Replies to Referee #1, GMD-2023-164

Xianwei Wu, Liang Hu, Lanning Wang, Haitian Lu, and Juepeng Zheng

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Thank you very much for your patient and detailed comments on our work [1]. These valuable comments are very helpful for us to improve this paper. After carefully reading all the questions, we have answered each of them and will make appropriate corrections in the revised version of our manuscript.

In this attachment, the blue paragraphs represent your comments, and the black paragraphs below are our corresponding replies.

1 Replies to major comments

Replies to major comments are as follows:

1. The manuscript structure, particularly the method section, needs to be reorganized to improve the compactness. There are several areas that require clarification. For instance, Algorithm 1 calculates the RMSE, but its definition is found in section 3.2.2. It would be more appropriate to move the definition to section 2. Additionally, in Line 4 of Algorithm 2, it is unclear whether the new parameters are obtained using CAND. Furthermore, it is not explained why the local-level surrogate utilizes Gaussian Process. In addition, it could describes the difference between the algorithm used in this work and the ASMO. Typically, optimization algorithms require hundreds of steps to achieve convergence, but in this work, only around 20 steps of local optimization are performed. It is hard to say the algorithms get convergence. It appears that the ASMO method can achieve local optimization more quickly. The conclusion is not convinced. The description of CAND is difficult to follow, particularly the calculation vs and vd, which is lack of calculation details. The cross validation describe can move from result section to the method section.

This comment contains multiple questions, we will reply these questions separately.

1).We will improve the structure of the study in revised manuscript according to the comments.

2).The new parameters are not obtained by CAND, CAND is just used for global-level surrogate model.

3).Unlike global-level surrogate-model, the local-level surrogate model is required to have a higher accuracy with fewer samples. So that construction method of the loacl model is more important. according to [2, 3] GP is selected to construct local-level surrogate.

Similar to the global-level surrogate model, we conduct a cross-validation for several method to construct local surrogate model, the results are shown in Figure 1:

We will add these results to the rivised manuscript.

4). The entire optimization process consists of over 20 steps. After obtaining the current optimal solution, there are several validation steps. Once these validation steps are completed, and no new optimal solution is found, we consider the current optimal solution as the final result of the optimization. In the figure, we illustrate the reduction in RMSE during the optimization process and the associated errors.

In terms of errors, it's possible that our method may indeed have slightly higher errors compared to ASMO in the end. However, our method demonstrates greater stability throughout the entire optimization process, with errors consistently maintained at a lower level. In contrast, AMSO exhibits initial oscillations in errors, indicating that our surrogate model remains stable. While our final error may be slightly higher than that of ASMO, we believe that in cases where the errors are relatively close, the reduction in the number of optimization iterations is a highlight of our method, resulting in resource savings.

5).The description of CAND is described in Algorithm 1:

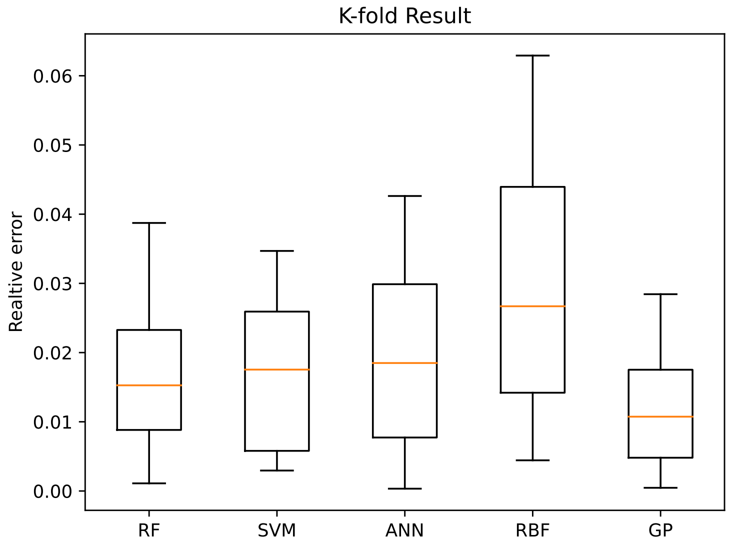

Figure 1: local model surrogate model cross-validation

Where, the Ω represents the random samples generated in this iteration process. $S(x)$ represents the predict value of point x generated by surrogate model. $\Delta(x)$ is the distance from point x to the current sampling point set A and y represents each point in set A.

We will add these to the revised manuscript.

6).We will move the cross validation to section method according to your comment.

2. The manuscript lacks a thorough mechanism analysis of how parameters affect precipitation on a global and regional scale. While section 4 presents optimization results, it lacks organization and falls short in providing a detailed understanding of the underlying mechanisms. To enhance the manuscript, it is recommended to delve deeper into the analysis. By investigating the cause-effect relationships between parameters and precipitation patterns, physics insights can be gained to improve the parameterization scheme.

1).The purpose of this work is to improve the CAM5 precipitation simulation result accord to parameter tuning method. rather than analyzing the mechanism. We believe that the goal has been achieved and it is a complete work. In this paper, we propose a surrogate model based method which can quickly calibrate parameters, and improve CAM5 precipitation using the multi-level surrogate model method and non-uniform parameterization schemes. We find a more suitable set of parameters for each region.

2).We do not change the physical processes in the parameterization scheme, we only changed the values of the parameters, or different values in different regions. We believe that these positive improvements achieved by changing the values of the parameters. In [4], there is more introduction to the mechanism, We also refer to this work when selecting parameters and determining the range of these parameters. We will try to explain these effects from the parameter value changes.

3. In equations 10-11, it could be possible for the numerator to be very large, and the denominator can be very small. This implies that the value of sigma could exceed 0.75, but the fitness is bad. If the fitness is good, the value of sigma could be close to 1 rather than just being greater than 0.75.

In order to confirm the radius of the trust region, we some works about trust region [5, 6], the update parameter $\eta1, \eta2$ are both less than 1 and they satisfy $0 < \eta1 < \eta2 < 1$. In this paper we set $\eta1 = 0.25$ and $\eta2 = 0.75$. If the $\sigma > 0.75$, we consider "increase the radius if the change is very successful , $\sigma \geq \eta2$ "[7]. In our method, the surrogate model ensures a certain level of accuracy, preventing scenarios where the numerator significantly outweighs the denominator.

4. Improving the clarity of motivation for the nonuniform parameter parameterization scheme.

In this paper, the motivation for the nonuniform parameter parameterization scheme is as follows:

1).It is well known that CAM5 is a well tuned model, however globally optimal parameters do not

Algorithm 1 Candidate point strategy

Compute $s^{max} \leftarrow \max_{x\in\Omega} s(x)$ and $s^{min} \leftarrow \min_{x\in\Omega} s(s)$

for each $x \in \Omega$ **do**

$$V^S(x) = \begin{cases} \frac{s(x)-s^{min}}{s^{max}-s^{min}} & if\ s^{max} > s^{min} \\ 1 & else \end{cases}$$

Calculate corresponding value of objective function for each sample.

end for

for each $x \in \Omega$ **do**

$\Delta(x) = min_{y\in A} d(x, y);$

end for

Compute $\Delta^{max} \leftarrow \max_{x\in\Omega} s(x)$ and $\Delta^{min} \leftarrow \min_{x\in\Omega} s(x)$

for each $x \in \Omega$ **do**

$$V^D(x) = \begin{cases} \frac{\Delta(x)-\Delta^{min}}{\Delta^{max}-\Delta^{min}} & if\ \Delta^{max} > \Delta^{min} \\ 1 & else \end{cases}$$

end for

return $argmin_{x\in\Omega} wV^S(x) + (1-w)V^D(x)$

necessarily mean they are the best solutions for every region.

2).Regional optimization experiments demonstrate that some regions have optimal parameters, leading to better results than default parameters.

3).Our experiments show that there is a "rocker effect" in the influence of parameters on precipitation. The same parameter values have different effects on different regions, making it challenging to optimize precipitation for all regions using a single parameter.

In summary, we proposed the nonuniform parameter parameterization scheme.

5. Line 55, while previous methods involved running the climate model, it is important to note that this work also requires running the climate model in each iteration. However, the manuscript does not provide a direct comparison of the efficiency of this method with other approaches. To enhance the evaluation of the proposed method, it would be beneficial to include an assessment of the computational cost compared to existing methods. This evaluation can provide valuable insights into the efficiency and computational advantages of the proposed approach, strengthening the manuscript's contribution in terms of computational performance.

We are very willing to conduct some performance-related comparisons. However, for some commonly used parameter optimization algorithms, such as DE, PSO, GA, and so on, using these methods for parameter tuning in CAM can yield relatively good results. Nevertheless, these algorithms require more computational resources and time during execution, which makes it challenging to evaluate these methods based on performance.

Considering computational resources and time costs, we compared our method with the AMSO algorithm. The ultimate advantage in performance is the advantage in the number of iterations.

2 Replies to minor comments

Replies to minor issues are as follows:

1. The title uses CAM5, but the contexts use CAM. They could be consistent.

We will use consistent definition of CAM5 and other technical terms over the whole manuscript.

2. Line 11: "selected points.." to "selected points."

We will correct it in revised manuscript.

1. Line 29: traditional tuning methods in climate modeling have certain limitations. However, they remain highly useful. The majority of climate models employ traditional tuning approaches due to their reliance on well-established physics knowledge. In fact, automatic tuning methods require a solid understanding of physics to enhance their efficiency.

We agree with your comment that manual parameter tuning remains necessary. This is because optimizing the parameters of atmospheric models requires a solid understanding of the underlying physics. Our proposed method is not intended to completely replace manual tuning but to enhance the efficiency of optimization. It is built on a foundation of substantial knowledge about the model. Using automated optimization methods, we aim to improve the tuning efficiency and reduce the consumption of computational resources. Perhaps the term "less useful" is not quite accurate. We will reconsider and use a more appropriate word to express our viewpoint.

2.Line 35, The statement that "WRF physics process is simple" is not accurate. In fact, it is known to be complex and intricate.

We agree with your comment. WRF is indeed a complex model that involves many intricate physical processes. The confusion may have arisen from our choice of words. What we are trying to emphasize is not the complexity of the model but rather that WRF is geared towards local execution and short-term forecasting, which generally incurs lower resource costs for repeated runs. In contrast, CAM5 primarily focuses on global, long-term simulations, which result in longer execution times. Therefore, when it comes to optimizing parameters for CAM, it's challenging to apply methods involving many iterations. We will replace the ambiguous terms in line with your comment.

3. Line 37, The statement that "MVFSA may become infeasible for CAM tuning" may require further consideration. Fast simulated annealing, which is utilized in MVFSA, actually requires only one population to search for the next optimal parameters. The MVFSA requires thousands of steps to get a stable solution. But CAM requires a lot of computational cost for each optimization iteration. The authors should thoroughly discuss the challenges associated with MVFSA to provide a comprehensive understanding of its feasibility for CAM tuning.

The term "infeasible" does not imply that these methods cannot be used for parameter tuning of CAM, as mentioned in the comments, MVSFA requires thousands of iterations. After these iterations, a better set of parameters can be obtained. However, from an efficiency perspective, even though this method can yield improved parameters, the computational cost and time required for thousands of iterations are deemed unacceptable. Therefore, in this paper, "infeasible" not only refers to the capability for optimization but also encompasses whether better parameters can be obtained through optimization within acceptable resource costs.

4. Line 51, When the optimization process reaches convergence, further iterations do not lead to any improvement. Similarly, once the optimization algorithm has obtained a local solution, additional iterations do not result in further enhancements. The effectiveness of the algorithm is also a determining factor in this regard.

We agree this comment. Typically, in the normal operation of an algorithm, the optimal solution improves as the number of iterations increases. However, in some cases, increasing the number of iterations may not yield any better results. This can happen when the algorithm gets stuck in a local optimum, as mentioned in the comments, or when it has already converged. We will modify this sentence to make it less absolute in revised manuscript.

5. Line 58, It is confusing that 'the mathematical expression is complex and time-consuming'. Could you explain it?

This sentence contains a punctuation error. We will rewrite it in reviesd manuscript.

6. Line 59. Revise the sentence "Wang et al. ... ; a SCM-SMA hydrologic model"

We will rewrite this sentence in revised manuscript.

7. Line 85, the authors could carefully analyze the challenge of ASMO used in atmospheric model. The method has been successfully used in WRF, CLM. what's the real challenge for atmospheric model?

Compared to WRF, CAM focuses on long-term global-scale simulations, while WRF is designed for short-term regional-scale simulations. Consequently, CAM has higher computational costs, necessitating more efficient optimization methods. CLM is primarily employed to simulate land surface processes, while CAM is predominantly used for atmospheric processes. They encompass numerous distinct physical processes and parameterization schemes, resulting in substantial differences between the models.

While ASMO has been successfully applied to models like WRF and CLM, its application to CAM remains a challenge.

8. Line 91, the above sentences discuss the tuning algorithms. The sentence "The precipitation process ..." talk about the metrics. It would be beneficial to separate these statements into individual paragraphs.

Yes, These sentences talk about challenge of surrogate model for precipitation parameter tuning, we will separate these statements into individual paragraphs in revised manuscript.

9. Line 110, it is hard to say the nonlinearity and complexity of CAM5 are much higher than WRF.

We agree with your point. Perhaps it's not straightforward to conclude that the nonlinearity and complexity of CAM are necessarily higher than those of WRF, as both involve a significant amount of computation and complex physical processes. We will rephrase this sentence accordingly.

10. Section 2.1, describe more details of CAM5, such as horizontal resolution, vertical level, how long does CAM5 run, the sst and sea ice are used prescribed seasonal climatology.

We will add more description about CAM5 in revised manuscript.

11. Line 138: define the six main regions, giving a table including the range of latitude and longitude.

In the manuscript, the Table 1 we introduce the region selected in the study and we will add the cite of the table in revised manuscript.

12. Line 143, why not use GPCP to estimate precipitation but use ERA5.

Both ERA5 and GPCP can be used for precipitation analysis. However ERA5 provides higher-resolution data. So that we select ERA5 to estimate precipitation.

13. Line 147, "Makes" to "makes"

We will correct it in revised manuscript.

14. Line 163, is the "sampling method" is the latin hypercube sampling? How many samples do you conduct?

Yes, the "sampling method" is latin hypercube sampling. There are 60 samples we conduct. They are described in section 3.2.1.

15. Line 280, use the correct ref for GP.

We will add the correct ref for GP in revised manuscript.

16. Line 308, It is confusing that the surrogate model is built as the quadratic function. Does it use GP?

We use the GP to construct the local-level surrogate model, the "quadratic function" means that in the initial mathematical theory of trust region , a quadratic function is used to fit the real function.

17. For fig2, what is the y-axis? Is it the relative error? How calculate it?

the y-axis represents the relative error between the predict value and real value, it is calculated based on Eq.1:

$$relative\ error = \frac{|precdictvalue - realvalue|}{realvalue} \tag{1}$$

We will revise this paragraphs according to this comment.

19. Section 4.1.3 should be merged into section 4.1.2.

We will reorganize the structure according to the the comment and other comments about the structure.

20.In figure 4, it should include the obs pattern, or the difference between opt/default and observation.

We will add new results figures in revised manuscript according to this comment.

21.Line 366, it is confusing for this sentence "Therefore, we need to further . . . "

In previous sentences. We illustrate that the result of global-based tuning is not significant, some regions still need to be tuned. So that we try to find the best way to use the proposed method to improve the simulation result. Perhaps our choice of words was not precise. We will use more accurate term in this sentence.

References

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